

Quick to be Selfish or Quick to Cooperate?
A Meta-Analysis of Reaction Time Asymmetries in Social Decision-Making

Undergraduate Research Thesis

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Abstract

Dual-process theories classify a fast, automatic “System 1” and a deliberative, controlled “System 2” as distinct mechanisms driving human behavior. Several recent studies have used a classic experimental economics scenario, the public goods game (PGG), to link these systems with participants’ tendency to act cooperatively. This research attempts to measure patterns of intuition and reflection by tracking an individual’s decision time when donating to a common pool. These donations are multiplied by the experimenter and then redistributed equally among the group. Some authors find that cooperative participants make fast decisions, arguing that cooperation is thus intuitive. Meanwhile, other authors find the opposite correlation, claiming that selfishness is intuitive. Our analysis critiques both views by offering an alternative explanation, which is that response time results are driven by the cost of being cooperative. Here we test this hypothesis using data collected from a series of publications on the PGG. These findings provide evidence for our “strength of preference” hypothesis, namely that cooperation is fast when it is low cost and attractive, while cooperation is slow when it is high cost and unattractive. Therefore, we conclude that fast decision times can indicate individual preferences for varying donation efficiencies. These results offer a coherent story to a large body of seemingly incoherent findings.

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“Human behavior stems from three sources: desire, emotion, & knowledge.”

- Plato

“The opposite of a correct statement is a false statement. But the opposite of a profound truth may well be another profound truth.”

- Niels Bohr

“Don’t hate the player, hate the game.”

- Ice T

1. Introduction

A foundation of economics research argues for an instinctively selfish model of human behavior – one in which we must overcome our own egotistic motives in order to cooperate with another person. An emerging body of research claims that acting prosocially, rather, is the automatic behavior in social dilemmas and thus we are required to deliberate on our initial decisions to make the more selfish choice. This research is backed by data on reaction times (RTs), which measure the length of time a player will take to perceive, consider, and select a choice option. However, contradictions in the two claims described above have led to skepticism about the assumptions formed from using such methods. Are the RT claims generated from many experimental economics studies valid, or does there exist an alternate explanation for the asymmetries in their results? Moreover, how can we interpret RT data to better understand the processes involved in strategic decision making?

In recent decades, several prominent studies in the field of behavioral economics have linked RT with the dual-system model of behavior. This category of decision modeling, referred to more generally as dual-process theory, claims that choice behavior is a function of two systems: a rapid, intuitive decision process and its slower, deliberative counterpart (Kahneman, 2003). A central question in the exploration of this theory is how to interpret RT data in the context of social preferences. Although pervasive in the domain of experimental economics, social preferences take on a variety of forms in different game settings. Two general classifications of these preferences are 1) “egotistic” or “selfish”, and 2) “cooperative” or “pro-social”. In most cases, a selfish player is more concerned with maximizing their own payoff than that of the group or their opponent. Meanwhile, a player who is prosocial will typically

select the option that is “fairest”, the reciprocal action, or (in rare cases) the option that maximizes the opponent’s payoff (Fehr & Schmidt, 1999).

The variability in these settings can be traced back to experimental parameters, differences in task experience, priming effects, and incentive structures, among other variables. Noisy data especially complicates the analysis of RT studies in comparison to its impact on traditional procedural decision models. For example, failing to control for subjective value differences between and within individual games can create pseudo-correlations in players’ RT patterns (Krajbich et al., 2015). Another difficulty is that a single reasoning process may actually direct choices, and in this case decision conflict is driven by exogenous factors, such as perceived differences in the choice set (Osman, 2004) rather than endogenous dual-system processes. Choice models such as the drift-diffusion model of behavior predict that an individual’s strength of preference and RT are inversely related, and this means that longer RTs signify preferences which are closer to indifference between two options in a choice set (Chabris et al., 2008). Nonetheless, several groups of experimenters have used RT data to define fast behaviors as intuitive processes, and slower behaviors as deliberative. Many empirical studies have accepted this reasoning, and hence many of these authors interpret patterns in RT data as evidence that the players making the fastest choices are significantly more cooperative in game settings, while the slower group can be classified as selfish. Yet, other authors have produced data that leads to the opposite conclusion: egotistic players choose more quickly and their prosocial counterparts are on the slower side.

These starkly different claims prompt two important questions that I will answer in this meta-analysis:

i) How might we account for such heterogeneity in the empirical evidence with a single model? For example, the strength-of-preference model proposed by Krajbich et al. (2015) predicts separate RT trends across different game parameters, even within the same group of participants. This is because it takes overall contribution rates into account.

ii) What does this imply for our interpretation of RT data in future studies? Experimental evidence from the field of psychology has long utilized RT data, and behavioral economics research has only more recently explored this variable within existing paradigms of economic behavior. Future directions for RT studies are likely to include work in neuroeconomics, and thus it is crucial that researchers are equipped with an accurate method for interpreting the data.

1.1 Origins of a Dual-Process Theory

The first known speculations of a dual process theory began nearly a century ago, with Sigmund Freud's proposed distinction between 'primary' and 'secondary' processes of the mind. The former suggested that a system of unconscious thought was responsible for the repressed desires and impulses brought to fruition in dreams, while the latter operated by a more logical, rational framework during consciousness (Freud, 1921). Freud describes the primary process as one that is initially present in a living being, whereas the components of the secondary process develop over its lifetime. Such a theory was not without flaws, especially in the domain of evolutionary biology (Epstein, 1994), though updates to the two-system idea did not surface until the late twentieth century. Cognitive-experiential self theory (CEST) provided evidence of both an "automatic" and a "rational" mode of thought (Epstein, 1994) through numerous examples such as conflicting assessments between "the head and the heart", obtaining information from

textbooks versus acquiring knowledge from experience, and including anecdotes in order to effectively (and affectively) convey a particular message (Kahneman & Tversky, 1973). Others brought updates to the theory by investigating a rivalrous nature between the systems of intuitive and analytic thinking (Hammond, 1996) and adding characteristics to distinguish the two types of cognitive processing (Stanovich and West, 2000), as shown in **Figure 1** (from Kahneman, 2003), below.

Note here that Daniel Kahneman, who is credited with developing and refining the two-system view (2003), or “dual-process theory” as it is often referred to today, originally defined the fast, automatic “System 1” decisions as impressions: perceptual and rather involuntary. Contrarily, decisions under the domain of “System 2” were better described as judgments: intentional, deliberative, and controlled (Kahneman, 2003). The magnitude of control System 2 exhibits (given a range of decisions) can vary substantially, however. Often an individual will display judgments that resemble our perceptual state of mind, and the term “intuitive” is applied to these choices.

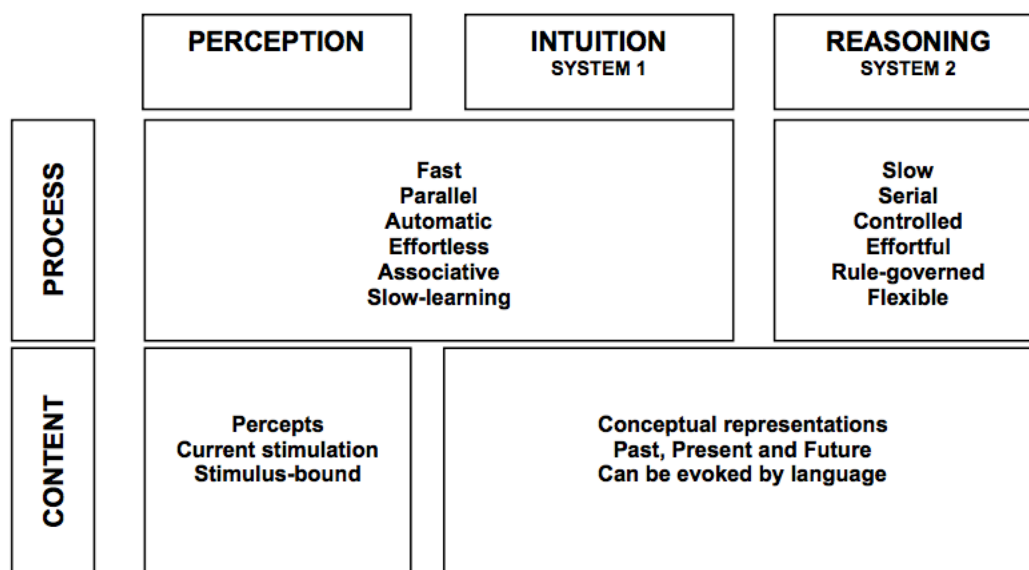


Figure 1 | Characteristics of Systems 1 & 2 (from Kahneman 2003)

More recently, authors have provided their own classifications of what an “intuitive” response might be in an experimental economics setting (Rubenstein, 2007; DiGuida and Devetag, 2013). These include, but are certainly not limited to: steps to reaching Nash Equilibrium, strategy of selfish individuals, strategy that leads to a fair outcome, strategy that yields the highest payoff for an individual, or a strategy with the lowest variance across an individual’s chosen outcomes. Given the variability of tasks and games used in social dilemma experiments, defining an instinctive response to a choice set will vary greatly across contexts (Spiliopoulos and Ortmann, 2015). Attempts to further define an intuitive response in various social dilemma scenarios has sparked a recent debate among authors who use reaction times (RTs) as an indicator of dual-system framework. We will explore these specific RT studies in depth throughout the remainder of this analysis.

1.2 The Reverse Inference Critique

Use of RT measurements in behavioral experiments dates back to before the existence of the dual process theory described above (Donders, 1868). However, the vast majority of this research literature is concentrated in the field of cognitive psychology (Spiliopoulos and Ortmann, 2015), rather than economics. Past researchers in the domain of experimental economics have even speculated that choice-maximizing behavior is independent of an individual’s decision making process, and hence, their RT (Friedman and Savage, 1948; Friedman, 1953). Decades later, others argued the opposite mechanism, in which decision-making processes play a substantial role in choice outcomes (Simon, 1976, 1986). Perhaps more importantly, these and later authors claim that optimal or rational decision behavior is not only a

function of choice outcome, but of the associated parameters and their adapted decision processes (Gigerenzer et al., 1999).

Current dual-process theory literature often employs RT measurements of players in various social dilemma scenarios in order to explore these decision-making processes. The framework underlying such experiments has led several authors to the conclusion that RT allows us to classify choices as “intuitive” System 1 reactions when they are fast, and “deliberative” System 2 responses when they are slow. Yet, social scientists must use caution in applying this inference within the domain of RT. While dual-process theory does suggest that an automatic process will occur faster than its deliberative counterpart, the reverse argument is not necessarily true. A more specific explanation of this conclusion, termed a reverse inference, is given by Krajbich et al. (2015) as follows:

There is a key distinction between the prediction that an automatic process will occur faster than more deliberative computations, and the classification of a choice as intuitive or automatic because it happens more quickly.

Keeping this warning in mind, I attempt to resolve the conflict posed by contradictions in previous RT experiments by analyzing the same data after controlling for subjective value differences. In the next section, I provide a more detailed outline of the relevant RT asymmetries found in the empirical literature, as well as an updated paradigm for existing data. The methodology and results in sections three and four expose our criteria for inclusion, data collection processes, and calculations for the included variables. Finally, the fifth section highlights additional details of the included studies, as well as future directions and limitations for RT research.

2. Empirical Background

2.1 Overview of Dual-Process Model Asymmetries

Shortly after the formation of Kahneman's dual-process theory in the late twentieth century, models of human decision-making in behavioral economics literature began to form extrapolations of a dual-system model in game theory settings. One of the first original experiments to expand on the concept of measuring RT used thousands of responses from an online decision game in order to further explore the role of RT on choice behavior (Rubenstein, 2007). Originally, Rubenstein formed three classifications for players' actions in social decision-making scenarios: cognitive, instinctive, or reasonless. He explicitly states that these were *assigned intuitively*, and likewise, the RT of an intuitive action is shorter when compared to its cognitive counterpart. Hence, experimental economics literature began to further analyze prosocial behavior using players' RT patterns in strategic game settings (Rand, Greene, & Nowak, 2012; Evans, Dillon, & Rand 2014; Lotito, Migheli, & Ortona, 2013; Branas-Garza, 2007; Cappelan 2014; Nielsen et al. 2014; Recalde et al. 2014). Although many of these researchers have produced robust relationships between RT and contribution rates in games such as the public goods game, their methods for employing RT may be unsuitable for making explicit inferences about the decision process.

The standard linear public goods game (PGG) is played among four or more individuals; each of the n players is endowed with an equal number of y tokens that they may either keep for themselves or invest some number of tokens, g_i , in a central fund ($0 \leq g_i \leq y$). After the players have simultaneously allocated their tokens, the central fund is multiplied by a pre-

determined factor, often called the ‘multiplier’. The resulting amount is redistributed equally among the four players. The term ‘marginal per capita return’ (mPCR) refers to the fraction of a player’s initial allocation to the group, a , that is returned to him or her at the conclusion of the game (see **Figure 2, A1 of Appendix**, for further details). Hence, a representative payoff function (Fehr & Gächter, 2000) is as follows:

$$(1) \quad \pi_i^1 = y - g_i + a \sum_{j=1}^n g_j,$$

$$0 < a < 1$$

For example, PGG studies in this analysis typically use payoff functions of the following form:

$$(2) \quad \pi_i^1 = 40 - g_i + 0.5 \sum_{j=1}^4 g_j$$

in which group size is four players, initial individual allocation is 40 tokens, the multiplier is two, and the mPCR value is thus 0.5. In this particular instance, the sum of all contributions is given by $\sum g_j$ and each individual’s mPCR is 0.5 tokens per token contributed. Standard assumptions of economic behavior predict that individuals will free-ride, or allocate zero of their initial tokens to the group fund; this is the dominant strategy for the PGG. Decades of PGG and game theory research suggest other motives, however.

Experimenters model players’ decision processes with ideas from dual-process theory to provide further rationale for prosocial and selfish motives. These models largely assume that decisions can be labeled as intuitive or deliberative given the players’ RT distribution. For

example, a recent experiment (Rand, Greene, & Nowak, 2012) found faster subjects contributing more on average in public goods games, and thus the authors conclude that people overall may have a predisposition to act cooperatively. Likewise, Lotito et al. (2013) employ RT data during the PGG in a similar fashion, arguing that as RTs decrease, the action of a player becomes more intuitive. While the authors note that average RTs are similar across groups, they find: i) a negative correlation between RT and contribution, and ii) decreased contributions in later rounds of the game. Cappelán et al. (2014) notes that players seem to have an instinctive drive to act fairly in Dictator Games. Once more, this inference is drawn from the idea that participants who chose fair divisions of the allocation in Dictator Games had significantly shorter RTs than those who chose the selfish option. These studies claim humans are therefore predisposed to act fairly and infer that a fast response implies an intuitive action.

On the contrary, several researchers (Lohse, Goeschel, & Diederich, 2014; Piovesan & Wengstron, 2009; Verkoeijen and Bouwmeester, 2014; Fielder et al. 2013; Tinghog, 2013; Kuss et al., 2015) claim that since egoistic choices are fast, these choices are thus “intuitive”. Lohse et al. (2014) describe cooperative choices as being associated with deliberative processes, as participants who contribute the least make the quickest decisions in a binary PGG scenario. The study does emphasize the idea that type and context of a public good may drive differences in contribution rates, which is discussed here in later sections. In a series of high, low, and mixed inequality Dictator Games, individuals make faster decisions when these maximize their own payoffs, rather than display preferences for prosociality (Piovesan and Wengstrom, 2009). Furthermore, their results show that faster subjects overall tend to make more egoistic choices. Fiedler (2013) uses a Social Value Orientation (SVO) slider and eye-tracking to compare their results. A version of the SVO slider is included in the appendix of this document (see **A2**,

Figure 3) for further reference. They report that as players indicate higher levels of prosociality on the SVO slider, their RTs in the one-shot and repeated PGG also increase.

Evans, Dillion, & Rand (2013) look further into the inconsistent RT literature results using a prisoner's dilemma, one-shot PGG and repeated PGG. They test a hypothesis that decision conflict, defined by the authors as an unclear preference for any particular option in a social dilemma, drives longer RTs. The series of experiments indeed displays evidence for an inverted-U pattern of RTs, meaning that decisions classified as “extremely” prosocial or selfish will have the shortest RTs, and players who make more intermediate contribution decisions take the longest to decide. While this study represents an important step towards correctly interpreting RT patterns, it reveals an additional caveat in the experimental design: RT differences may depend on not only the subjects we have, but the questions we ask.

Krajbich, Bartling, Hare, & Fehr (2015) were the first to investigate this problem by purposefully altering experimental parameters in social-preference and intertemporal choice paradigms. They replicate the PGG experiment by Rand et al. (2012), but include two other mPCR values in addition to the value used in the original study design (0.5). Furthermore, they hypothesize that contributions and RTs are positively correlated when overall contribution rates are below 50%, and likewise, they predict a negative correlation between contribution and RT when the overall amount is above 50%. By creating different levels of group benefit, they show that varying the attractiveness of contributing to the group fund does indeed alter average contribution rates. Participants contributed an average of 25%, 47%, and 63% in the 0.3, 0.5, and 0.9 mPCR rounds, respectively. Moreover, the faster half of participants in the 0.3 condition contribute less than the slower half; this trend is also seen in the 0.5 condition. The 0.9 condition is also consistent with the original hypothesis, as the faster half of participants instead contribute

more than the slower half. Namely, these results support the authors' strength-of-preference account, rather than a dual process account which predicts either strictly positive or strictly negative correlations between contribution and RT in all three cases.

2.2 The Case for Preferences and Parameters

While reaction times can offer valuable insights on choice behavior, these are more accurate in scenarios where players' perceptions of choice similarity are properly accounted for. The majority of dual-process explanations assume that RTs from a single choice function allow us to extrapolate an individual's temporal decision behavior as a causal explanation in *any* given choice scenario. Given the inconsistency in current RT data, this assumption would be largely inaccurate, and yet many dual process accounts support a strictly negative or positive correlation between contribution and RT. How, then, can we account for the asymmetry in RT results? Such a framework places too little weight on the parameters of the initial choice scenario, and hence, fails to encompass the average perceived utility of the choice for the group as a whole. Our strength-of-preference explanation offers a more cohesive explanation for the link between RT and prosociality. We hypothesize that participants' RTs are correlated instead with the parameters of a social dilemma, *given* their baseline preference for prosociality. A concrete example of this choice process is as follows:

Consider a scenario in which we observe a group of individuals at a department faculty meeting. The meeting takes place midmorning on the same day each week, and faculty members take turns bringing coffee and juice and preparing it before the meeting begins. We assume that half of the group usually prefers to drink coffee while the other half prefers juice. One day the group realizes that the person responsible for bringing coffee is away at a conference, so they

have to brew some stale, generic coffee from the back of the cupboard. Most of the group decides right away to drink the juice instead, though a few sleep deprived researchers go for coffee after quite a bit more deliberation than usual. The next week, however, everyone is pleasantly surprised to find a full espresso bar set up in the meeting room to welcome guest faculty members visiting the university. This time, the (still) sleep-deprived coffee-lovers have cappuccinos before most people have even walked in the door, and most of the department follows eagerly behind. Even those few who still go for the juice hesitate before doing so.

Now, from the perspective of one of the visiting professors, it may appear that this particular department has an unusually high affinity for caffeine. On the other hand, if the same professor had been present a week before, they may have come to the opposite conclusion. Both scenarios involve a person's own taste preferences, and the degree to which the coffee actually looks appealing. When the coffee offered is cheap, the non-coffee individuals have no trouble deciding to turn it down, but the coffee-lovers make a decision much later. The reverse is true when the expensive coffee is presented. Note that coffee-drinkers do not always make a decision quickly, just as non-coffee drinkers do not always choose slowly, and vice-versa.

We can apply a similar framework to our PGG design. Let us assume that on average, 50% of participants exemplify selfish behavior (donating less than half of their private fund to the group) and 50% display prosocial behavior (donating more than half). Moreover, when the parameters of the PGG are closely aligned with either group's preferences, the individuals in that group are quicker to make a choice about their allocation to the group fund (Krajbich, 2015). For instance, versions of the PGG where participants may be disposed towards selfishness will likely show that those with a preference for selfish behavior have shorter RTs. The opposite is

true for a game with higher group benefit, in which the participants who are more prosocial on average are expected to have shorter RTs.

Based on this idea, I aim to separate studies based on their average contribution rates. Note that a cooperation rate of 0.5 is representative of a player who allocates half of his or her initial private amount to the group fund; in other words, this particular player is halfway between completely selfish (free-riding) and completely prosocial. An average cooperation rate below 0.5 can be attributed to studies with lower-group benefit, and we hypothesize that players who contribute less than the average amount will make quicker decisions in this scenario. Similarly, studies with an average cooperation rate above 0.5 suggest that the group benefit is higher, making contributing a more attractive option. Participants who contribute more than average will then make faster decisions here.

Few authors implement this framework when using the RT methodology described previously, though recent experimental economics studies have begun to critique reverse inference claims based on RT asymmetries reported in the literature (Krajbich et al, 2015; Kuss et al., 2015). Spiliopoulos and Ortmann (2015) characterize dual process models as “descriptive” models of behavior, rather than procedural, whereas the latter category implies that an explicit mechanism exists for switching between the two systems. For instance, dual process theory suggests that System 2 overrides System 1 (Kahneman, 2011). Any variance in how this process occurs, due to cognitive load, time constraint, etc., may partially account for the contradictions within empirical findings. In order to address the variability in the current literature, we conducted a comprehensive analysis with the following objectives: (1) to find a standardized measure for the independent variable of contribution level with the available data; (2) to

investigate and quantify any existing correlation between RTs and contribution rates in previous experiments; and (3) to explore parameters that influence these effects.

3. Methodology

This analysis looks at the relationship between group levels of prosociality and log-transformed reaction times. Pooling data across 15 studies, we assess a total of 9341 individual decisions.

3.1 Criteria for inclusion

We compile data from 15 different public goods games. Our dataset covers studies in which subjects (i) decided whether to incur some private cost to provide a greater group benefit, (ii) were separated into groups by decision time in which (iii) they were not subject to constraints or delays during the decision-making process. Next, we investigate reported patterns between log reaction time data and mean contributions.

The meta-analysis excluded studies that examined reaction times under time-pressure or time-delay scenarios (Rand et al., 2012; Tinghog et al., 2013). While studies in these categories can be valuable in examining interactions between RT and prosociality, previous work suggests that any form of time-constraints may alter the amount of information acquired or processed. Additionally, even perceiving some type of time pressure can impact choice behavior when it is not explicitly imposed in the experimental setting (Benson, 1993). Also, the meta-analysis excluded studies using forms of social dilemmas (i.e. Trust Games, Ultimatum Games, etc.) that

did not allow players to make simultaneous contribution decisions or use arbitrary measures of prosociality that cannot be measured on a discrete scale of contribution decisions. While the original search criteria did not exclude Dictator Games, the available experiments did not employ an independent variable that fit the standardized contribution scale. A flow diagram of the criteria is given below, in **Figure 4**.

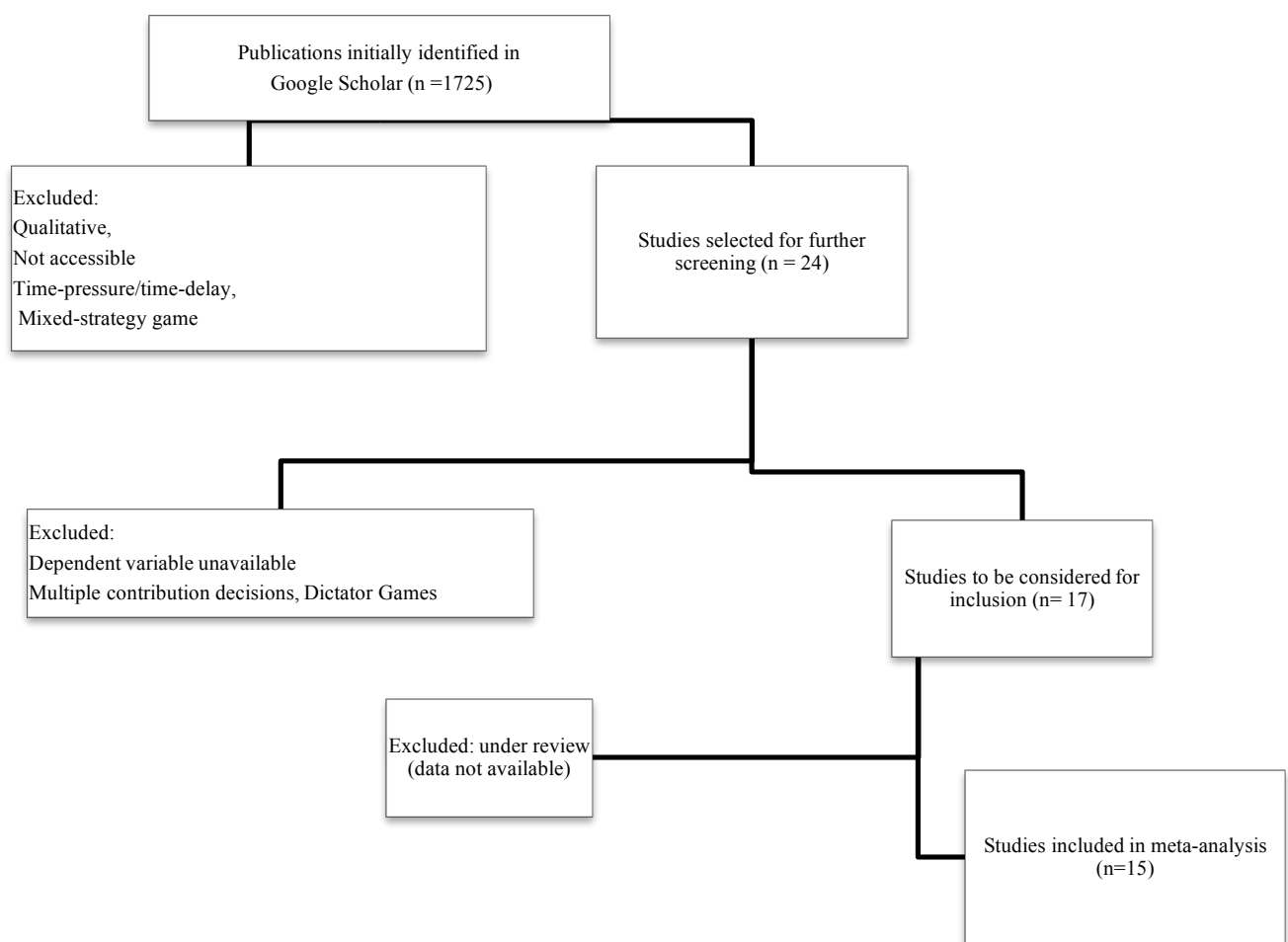


Figure 4 | Flow diagram of the eligible studies.

3.2 Information sources and search

We first performed a Google Scholar search using the keywords *dual-process*, *reaction-time*, *response-time*, *public goods game*, and *dictator game*, either alone or in combination with another term from the list. Studies were included from the first available date until November 1, 2015.

3.3 Data collection

We developed an electronic data sheet, extracted data from literature and supplementary material when available, and directly contacted authors for additional values that were needed in the analysis. Data collection was conducted for the first time in January of 2015, was refined in July of 2015, and updated in October of 2015.

3.4 Study characteristics

All of the included studies (**Table 1**) were some variation of the standard linear PGG. However, in relation to contribution level, the asymmetry among the results of reaction-time studies remains notable and persistent. While some authors claim that fast responses correlate with higher contributions (i.e. ‘prosocial’ behavior), others show a correlation between fast responses and lower contributions. These studies also vary in terms of cost to contribution via their mPCR values: a lower mPCR, for instance, makes contributing to the group costlier for the individual than a higher mPCR. To account for this framework, we have used each study’s mean contribution percentage (scaled from 0-1) as the independent variable. This range of

contribution values controls for the cost of contributing in each study. Our hypothesis suggests that studies with overall contribution rates below 0.5 will also display positive correlations between reaction time and contribution; studies with overall contribution rates above 0.5 will display negative correlations between reaction time and contribution. The selected studies also include data with which we or the authors have calculated a regression coefficient of $\log(\text{RT})$ on contribution level, and this value serves as the dependent variable, as shown in **Table 2**. Here, we provide further detail on the experimental parameters of each and outline calculations for inclusion in the meta-analysis.

1 st Author	Year	N	Experimental Conditions			
			Format	Choice	mPCR	Other variables
Rand	2012	212	One-shot	Continuous	0.5	
		192	Repeated	Continuous	0.5	Reward/punishment
		256	One-shot	Continuous	0.5	Priming
		338	One-shot	Continuous	0.5	Daily life interactions
		72	One-shot	Continuous	0.5	
Fiedler	2013	38	One-shot	Continuous	0.6	SVO slider
Lotito	2013	253	Repeated	Continuous	0.5	Priming
Lohse	2014	3484	One-shot	Binary	-	
		3484	One-shot	Binary	-	
Evans	2014	156	One-shot	Continuous	0.5	
		28	Repeated	Continuous	0.5	
		303	One-shot	Incremental	0.5	
Krajbich	2015	175	One-shot	Continuous	0.3	
		175	One-shot	Continuous	0.5	
		175	One-shot	Continuous	0.9	

Table 1 | Game format and variables among selected PGG studies.

Notes: mPCR – marginal per capita return. *Source:* Author data.

To begin, we include three experiments from Rand et al. 2012, with the first (**Table 2, A**) being a standard one-shot PGG (recruited using Amazon Mechanical Turk, [ATurk]) between four players, each endowed with \$0.40. The players answered two comprehension questions regarding their understanding of payoff structure and were then allowed to proceed with the game. Each player could donate any fraction of their allocation to the group fund, where it would then be doubled and re-divided evenly among the four players. If c_i = individual contribution to group and n = number of subjects, our contribution value was calculated with the following function:

$$(3) \quad C = \frac{\sum c_i}{n}$$

The mean contribution level was reported as 23.83 cents; this value was divided by the total possible contribution level (40 cents) to obtain our standardized contribution value of 0.5958. However, whereas in the original publication, the authors log10-transform decision-times to obtain the regression coefficient, we requested log-transformed (i.e. natural log) decision-times directly from the authors to include in this analysis. As previously noted, we consider prosocial individuals to be those who contribute above the study's mean contribution level.

In the same publication, Rand et al. also utilize a PGG experiment with the option to reward/punish other players (**B**) and that frames players' actions by requiring them to write a paragraph to promote or inhibit intuition, prior to playing the game. The rest of the experiment was identical to the PGG described above. Finally, the authors include a version where players rank how cooperative they rank their daily life interaction-partners to be (**D**). The authors use the same game format and include a post-experimental questionnaire in which they ask players,

“To what extent do you feel you can trust other people that you interact with in your daily life?” using a 10-point Likert scale from “1, very little” to “10, very much”. Finally, a supplemental study (**E**) from the Harvard CLER laboratory is included in which authors use the same PGG framework as the studies conducted with MTurk. Again, we obtain mean contribution value and the log-transformed regression coefficients directly from author data for each of the three studies above.

A later study by Evans et al. (2014) uses both a one-shot PGG (**H**) and repeated PGG (**I**) with two separate pools of participants from the Harvard CLER. The study participants could contribute between 0 and 400 points to the group fund, where it was doubled and redistributed evenly. This publication also uses a sample of participants from MTurk (**J**), but the PGG experimental design differs slightly from previously discussed studies in that they use radio buttons to contribute between 0 and 40 cents (in ten cent increments). Contributions were given to partners and then doubled. The mean contribution levels and reaction time coefficients were obtained from the authors for each of the three PGG; only the 1st round of the repeated study was used in this analysis for consistency.

Krajbich et. al. (2015) use a PGG format in which they vary the mPCR value over a series of three trials. Players were given an initial allocation of 40 points and allowed to allocate any fraction of this amount to the central fund. They made one decision at each mPCR value: 0.3, 0.5, and 0.9 (**M**, **N**, and **O**, respectively). The authors regressed logarithm of reaction time on contribution rate to obtain the value reported in **Table 2** (the log-transformed coefficients were not directly reported in the original article). Further, the mean contribution rates for each of the three conditions were taken from the original work.

Lohse et al. (2014) employ a PGG scenario through a large-scale online experiment (F). In their design, participants make a binary choice between a monetary reward (randomly drawn from a uniform distribution between 2-100 units of currency) and the elimination of 1 metric ton of CO₂ emissions. In this case, elimination of pollution is the pro-social choice. Each participant made two separate decisions, and both are represented here. The authors include a multivariate OLS regression of their RT data in which they control for potential confounds. They regress logarithm of reaction time on binary contribution decision given the various treatment conditions described above. Additionally, the study broke down decisions into four categories of very fast, fast, slow, and very slow. Mean contribution rates and regression coefficient values for log(RT) were taken directly from the literature results (with demographic controls included).

Lotito et al. (2013) assigned four treatment groups that combined the following scenarios: a) players either were i) acquainted before the experiment or ii) had no previous acquaintance, and b) players i) performed team work or ii) engaged in cheap talk directly before the experiment. The team work involved performing a budget analysis and report on three different companies. The cheap talk treatment asked players to chat for 20 minutes. The groups played a standard PGG with four players/group and an initial endowment of 60 experimental monetary units (EMUs); each EMU was worth 0.01 €. The participants each decided which fraction of the initial amount they wanted to contribute to the group fund, and the sum of these was doubled and redistributed evenly among the four participants. Unlike the studies previously discussed, this experiment (F) was a repeated PGG over ten rounds. The contribution levels were calculated using Equation 3 with the contribution means for each group, which are provided in the original publication. However, while the regression coefficient included does regress reaction time on

contribution level, it is important to note here that this is a panel tobit regression, and it does not employ log-transformed reaction times. We were unable to obtain this particular regression coefficient from the authors.

Fiedler et. al (2013) use a Social Value Orientation (SVO) measure (see **Figure 4, A2 of Appendix**), in combination with eye-tracking, to measure contribution decisions in a 3-person PGG (**G**). Each participant was endowed with 20 points and instructed to decide how much to contribute, c_i , to the group fund. All contributions to the fund, c_j , were multiplied by 1.8 and shared equally between all participants. They calculate final payoffs using a payoff function for a three-person linear PGG:

$$(5) \quad \text{Payoff} = (20 - c_i) + (1.8 \times \frac{\sum c_j}{3})$$

Since the mean contribution of the one-shot PGG was not explicitly stated in this study, we calculated this value, as well as the value for logRT on contribution, using author-provided data.

IV. Results

In this analysis, we examine existing dual-process literature with respect to the RT inferences made in the above studies. It is worth noting that experiments certainly differ in their explicit payoffs to the participant, but other factors, such as instructions, priming effects, etc. also influence the perceived cost of a given contribution decision. Our analysis is conducted using linear regression taking the correlation between log reaction time and prosociality as the dependent variable. Mean contribution amount (**Table 2**) is measured as percentage donation of

the players' initial allotment in each individual study. The mean contribution is standardized on a 0-1 scale where 0 represents maximum selfishness or free-riding, and 1 is equivalent to maximum prosociality or full cooperation. We employ mean contribution percentages to measure the perceived “cost” of contribution for varying game parameters. For example, a contribution percentage of 0.2 implies that game participants viewed the decision to contribute (i.e. the prosocial option) as less attractive on average than the more selfish option. Conversely, a mean contribution percentage of 0.8 would imply that prosocial behavior in a given choice scenario is less costly to the average participant.

Study	$\mu_{\text{contribution}}$	Coefficient	N	1stAuthor	Year	Other notes
A	0.5958	-0.3683	212	Rand	2012	Study 1
B	0.7115	-0.3334	192	Rand	2012	Study 5, reward/punishment
C	0.6146	-0.2453	256	Rand	2012	Study 9, priming
D	0.5965	-0.225	338	Rand	2012	Study 10, daily life interactions
E	0.5104	-0.3806	72	Rand	2012	Supplemental study, CLER lab
F	0.553	-0.129*	1152	Lotito	2013	Priming
G	0.536	0.1661	36	Fiedler	2013	Social Value Orientation (SVO)
H	0.447	-0.022	156	Evans	2014	Study 2
I	0.705	-0.355	28	Evans	2014	Study 3, 1st of repeated PGG
J	0.556	0.027	303	Evans	2014	Study 4, Mturk
K	0.1751	0.371	3484	Lohse	2014	Round 1
L	0.2312	0.124	3484	Lohse	2014	Round 2
M	0.25	0.609	175	Krajbich	2015	mPCR = 0.3
N	0.48	0.1751	175	Krajbich	2015	mPCR = 0.5
O	0.63	-0.1872	175	Krajbich	2015	mPCR = 0.9

Table 2 | Regression Data: Contribution values and reaction time coefficients, by study.
 μ_c = mean contribution (percentage value)

*Lohse et. al randomly drew a monetary amount between €2-€100; each participant was given a choice between a public goods contribution (i.e. reducing one metric ton of CO₂ emissions) or receipt of the random monetary reward.

We find a negative Pearson correlation between author-reported regression values (logRT on prosociality) and mean contribution rates ($r = -0.81$), as shown in **Figure 5**. The coefficient of the regression value is more positive in the case of smaller group contributions, and hence more negative as the size of the group contribution increases. This is consistent with our hypothesis that studies with overall contribution rates below 0.5 will also display positive correlations between reaction time and contribution; studies with overall contribution rates above 0.5 will display negative correlations between reaction time and contribution.

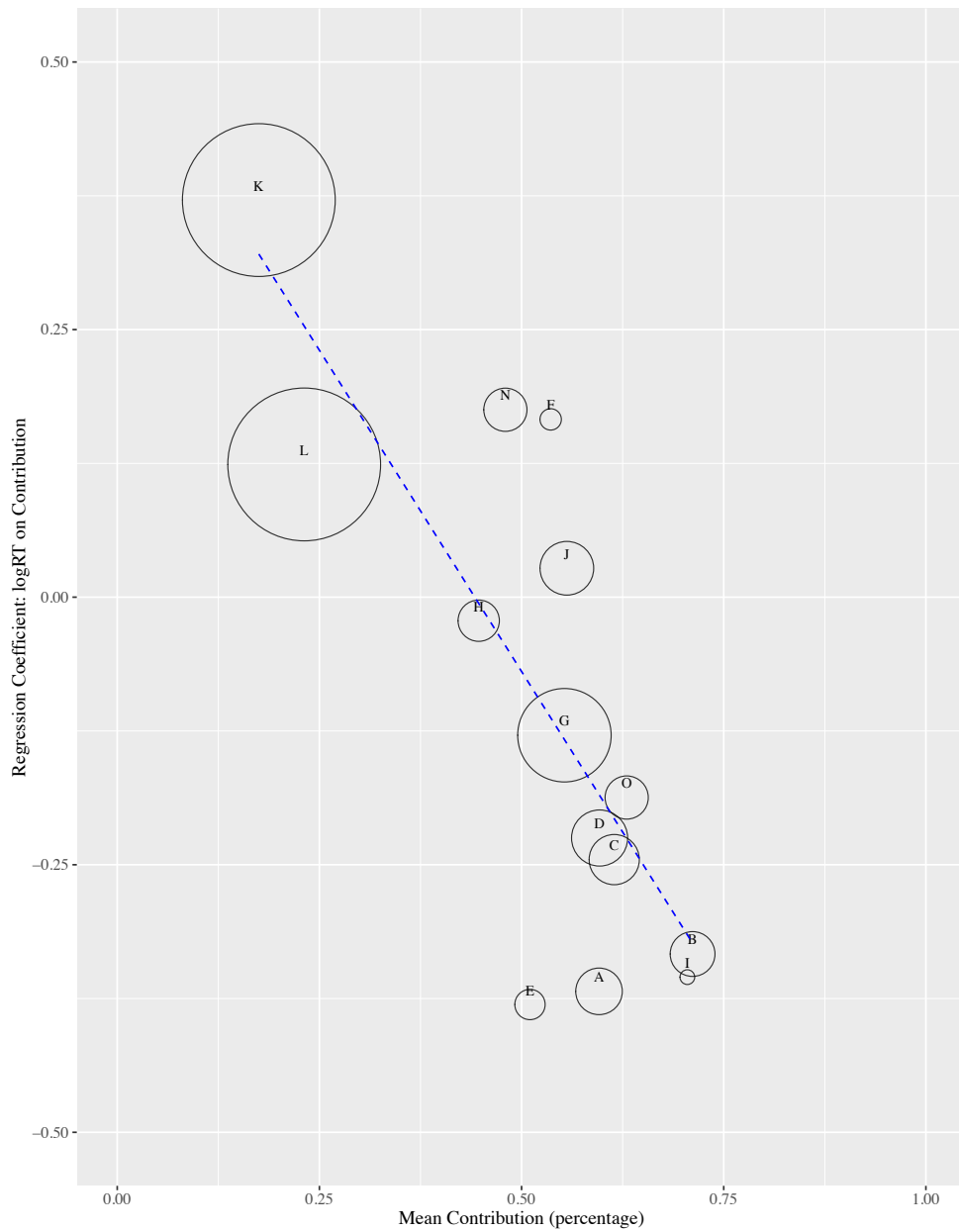


Figure 5 | Graphical representation reaction time coefficients and standardized average contribution rates

All regression values (logdecisiontime on mean contribution percentage) provided by authors. Data points scaled to number of study participants (see **Table 1**). ‘Prosociality’ defined as donating above the mean contribution in a given study (see **Table 2**). Pearson correlation = -0.81; Spearman correlation = -0.70. Graphic constructed with ggplot2 (H. Wickham, 2009).

As shown above, we resolve some of the discrepancy in RT literature by modifying the independent variable. Here we correct for utility differences by taking overall contribution rates

into account. This is consistent with our initial hypothesis that reaction times increase proportionally with increased cost of a particular choice.

V. Discussion

The result of this analysis suggests that there is no general correlation between RT and a player's tendency to choose the prosocial option. We do, however, accommodate for group preferences and parameters of each study by controlling for utility differences across subject populations. In groups that can be described as prosocial (contributing $> 50\%$ allocation to group fund on average) overall, the average corresponding reaction time is lower for players who chose the prosocial option in a respective decision scenario. Likewise, studies with group contribution averages on the selfish end of the spectrum ($< 50\%$ allocation to group fund) display decreased average RTs for players selecting the more selfish option.

One apparent conclusion from our findings is that the parameters of a choice paradigm may have substantial and relevant impacts on the timing and outcome of participant behavior. Beyond the strength of preference argument, these include task instructions, measures of group vs. individual benefit (i.e. mPCR), population type, accessibility, and other game format alterations. Information regarding a particular choice can be made more or less accessible due to factors such as stimulus salience, selective attention by the individual, and activation of a behavioral or cognitive response via priming (Higgins, 1996). It is critically important to keep in mind, then, that any minor alteration in an experimental design can invoke drastic changes in the behavior of participants who complete the experiment. For example, phrases in the instructions or “practice” examples (often used in social dilemma games) may play a large role in framing the

decisions of a person who is unfamiliar with that game. One study hypothesizes that participants with cooperative daily-life settings/partners will act cooperatively in a PGG and hence have shorter RT (Rand, et al., 2012). A subsequent PGG study by the same authors uses a priming task: before playing the game, the experimenters ask participants to either promote or inhibit intuition by writing a short paragraph corresponding to their group. This condition also shows evidence of shorter RTs for higher cooperation rates. Other studies use priming and do conclude that the behavior of the players depends on the framing of the situation (Branas-Garza, 2006; Lotito et al., 2013; Rand et al., 2014; Rand & Kraft-Todd, 2014). On the contrary, another group of researchers has participants choose between a random monetary reward and elimination of CO₂ emissions, and the faster choices fall proportionally towards the selfish option (Lohse et al., 2014). The authors claim that these results highlight two important factors in the experimental design: first, that the mPCR for climate protection is, in theory, lower than that of a direct monetary reward as it is split between a large number of beneficiaries. Further, that this choice scenario eliminates the aspect of strategic uncertainty that occurs in the standard PGG: participants have complete control over their own payoff, other than the random monetary amount. This research also raises the notion that future work in economics that aims to focus on decision processes should measure the extent to which experimental parameters impact individual preferences, a concept I have analyzed here.

This analysis does not include time-pressure or delay data in the results, though our warning against reverse-inference claims still holds true for such models. Verkoeijen and Bouwmeester (2014) examine patterns of cooperation in a series of time pressure and forced delay experiments with the PGG. They fail to replicate the “intuitive cooperation” results of Rand and colleagues, including the claim that intuitive contribution can be attributed to behavior

outside of the laboratory environment. The results call attention to the validity of self-reports, previous PGG experience, time intervals between PGG participations, and the structure of the game itself. Tinghog et al. (2013) also test the validity of a Rand experiment in which they obtain different results from the original study, a time-pressure/time-delay experiment in which Rand et al. report increased cooperation for subjects who complete the PGG under time pressure. Two flaws in this design were identified in the Tinghog article, the first being that excluding subjects who fail to make a decision in the allotted time cause a selection problem. The second, related flaw was that the original authors incorrectly control for subjects who met or did not meet the time requirement.

Thus, accurate interpretation of reaction time data in the decision science literature remains crucial as authors continue to utilize RT variables as a proxy for dual-system models within their specific domains. A recent study (Obrecht & Chesney, 2016) explores ‘deliberative failure’ by asking subjects to judge a specific scenario in which base-rate information and stereotype information support incongruent judgments. The authors have a group of subjects evaluate statements that contain base-rate information, claiming that a limitation of their work is assumption that such evaluation prompts deliberation. They go on to suggest that this might be confirmed by looking at reaction times.

The domain of neuroeconomics certainly holds enormous potential as a future contributor to the development of dual-process theory. Investigations of social preferences have been conducted using fMRI in scenarios involving prosociality (Decety et al 2004; Zaki & Mitchell, 2011; Emonds et al, 2014; Kuss et al., 2015). Several of these find significant activity in regions of the brain linked to subjective value, such as the ventromedial prefrontal cortex (vmPFC) and orbitofrontal cortex (OFC). Further, results from the study by Kuss and colleagues indicate

increased activity in the dorsomedial prefrontal cortex (dmPFC) when selfish participants made non-costly social decisions. The authors also report that while selfish participants usually were faster to decide in comparison to pro-socials, they did have increased RTs for the non-costly social decisions. These results highlight the efficacy of neuroimaging studies in refining our current models of the choice process.

In summary, the use of RT data and dual-process models to analyze social dilemma paradigms has generated noticeable controversy. Much of the conflict stems from the reverse inference claims explored here. We have reconciled a portion of these results by correcting for subjective value differences across experiments via a standardized scale of prosociality. This analysis provides a clear direction for future RT studies in the field of experimental economics. However, further work is required to explore similar trends in other game formats and using alternate incentive structures.

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Appendix

A1. Figure 2

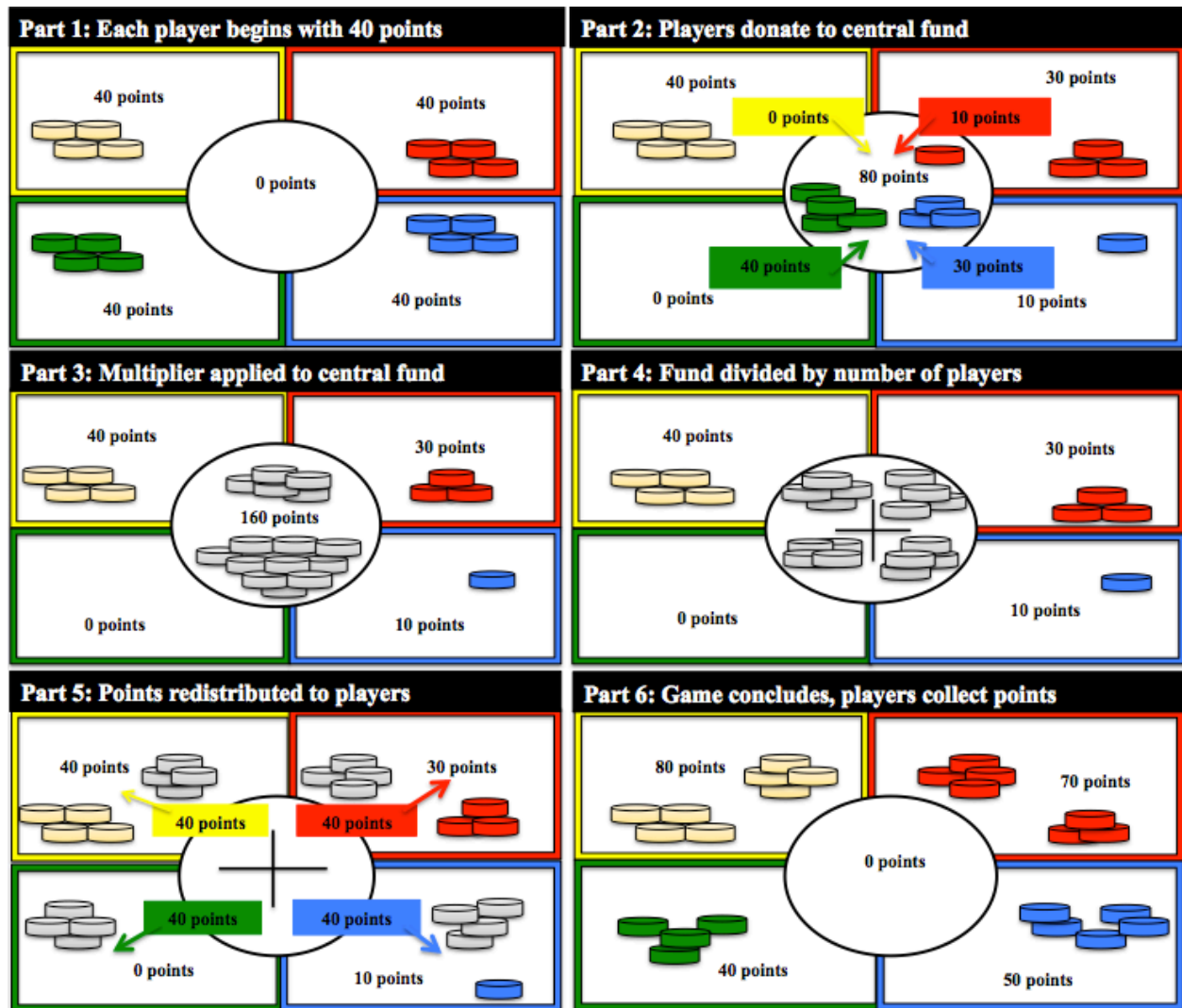


Figure 2 | Public Goods Game format (adapted from Lotito et al., 2013)

A2. Figure 3

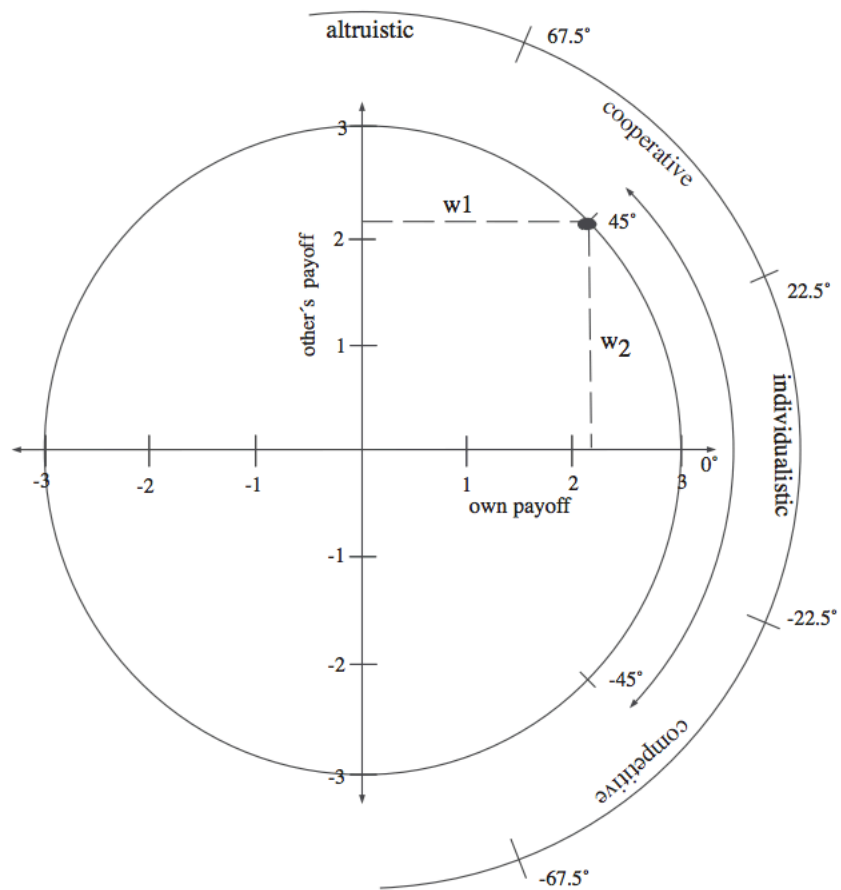


Figure 3 | Social Value Orientation Slider. (Original diagram from Fiedler et al., 2013)